Renewable and Sustainable Energy Reviews 41 (2015) 495–505

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

# A critical review of detection and classification of power quality events

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ARTICLE INFO

*Article history:*
Received 17 June 2014
Received in revised form
18 August 2014
Accepted 26 August 2014

*Keywords:*
Power system
Feature extraction
Power quality
PQ disturbance
PQ event classifier
Segmentation

ABSTRACT

Requirement of green supply with higher quality has been consumers' demand around the globe. The electrical power system is expected to deliver undistorted sinusoidal rated voltage and current continuously at rated frequency to the consumers. This paper presents a comprehensive review of signal processing and intelligent techniques for automatic classification of the power quality (PQ) events and an effect of noise on detection and classification of disturbances. It is intended to provide a wide spectrum on the status of detection and classification of PQ disturbances as well as an effect of noise on detection and classification of PQ events to the researchers, designers and engineers working on power quality. More than 150 research publications on detection and classification techniques of PQ disturbances have been critically examined, classified and listed for quick reference.

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**Contents**



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http://dx.doi.org/10.1016/j.rser.2014.08.070
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## 1. Introduction

Considerable changes in a business environment have increased the use of sensitive electronic components, computers, programmable logic controllers, protection and relaying equipments which have increased the power consumptions [1]. Increasing consumer expectations with the requirement of green supply around the globe, where integration of renewable energy sources to the distribution grid is the focus area of smart grid, electrical power systems are expected to deliver power supply continuously at high quality to the consumers. Economy of any country suffers with huge losses when there are voltage or current abnormalities present in the power delivery. Any deviation/disturbance manifested in the voltage, current and frequency from the standard rating is treated as a power quality (PQ) problem that results in failure or malfunctioning of electrical/electronic equipments [2]. Power quality disturbances increase the risk of blackout; especially because of the failure of interdependencies between sub-networks and associated dynamical propagations. To prevent these issues customers are willing to invest in the on-site equipments to ensure higher level of quality supply such as uninterrupted power supply (UPS) and stabilizers even though these are very costly [3]. It shows the importance of power quality towards economic distribution of the energy.

Renewable energy integration and smart transmission systems, well equipped with modern control equipments, increase the applications of nonlinear and electronically switched devices in distribution systems which exaggerate problems such as harmonics, flicker, voltage sag/swell, voltage regulation, load unbalancing and deviations in phase as well as frequency. Several solid-state electronic/power-electronic devices have been developed, studied and proposed to the international scientific community with the goal of improving supplied power quality in last two decades [4]. This causes increased operational and planning complexity of electricity supply networks which requires increased attention for quality of power supply [5]. The transient oscillations are also seen in power networks when power electronically controlled capacitors are switched across a node/bus.

The harmonics and power sinusoids modulated by low frequency signals are also observed in electrical networks due to sudden changes in the operating conditions such as load disturbances, network contingencies, and output of renewable energy sources [6–10]. These events may impose penalties to the consumers in terms of supporting ancillary services' cost such as cost of reactive power, re-dispatch cost and load curtailment cost to remove disturbing load. Therefore, PQ events need to be monitored and mitigated to maintain standard of supply and economic operating conditions. In complex and large power systems, during operations, a huge amount of measured PQ events data make analysis difficult for monitoring programs. Therefore, a smart tool and methodology are required for detection and classification of this data for clear and smart understanding to the utilities, regulators and customers about the operating requirements under sudden change of operating conditions [11]. In this regard, feature extraction and classification are the most important part of the generalized PQ event classification system where PQ event detection requires the feature extraction from the disturbances. To make analysis more effective; a set of better features should be available to report the disturbance signal efficiently [4]. Thereafter, this set of extracted features can be used for the classification process.

This paper aims at presenting a comprehensive review on the topic of power quality events detection and classification techniques/methodologies. Over 150 publications [1–171] are critically reviewed and classified into six major categories. The first [1–17] is on general power quality and their economics as well as standards. The second category [18–23] is on the automatic power quality events' classifier and general ideas of segmentation and feature extraction of PQ disturbances. The third category [24–87] includes feature extraction techniques which is sub-classified into Fourier transform based methods [24–36], S-transform based methods [37–44], Hilbert Huang transform based methods [45–54], wavelet transform based methods [55–69], and miscellaneous techniques [70–87]. The fourth category [88–164] is on artificial intelligent classification techniques which is further classified into support vector machine based classification [89–102], neural network based classification [103–115], fuzzy-expert system based classification [116–129], neuro-fuzzy system based classification [130–136], genetic algorithm based classification [137–145] and miscellaneous classification systems [146–164].The fifth and final category [165–171] is on the effect of noise on PQ events' classification. However some publications include more than one category and have been classified based on their dominant field.

This paper is divided into nine sections. Starting with an introduction in Section 1, Section 2 describes power quality and Section 3 covers the automatic power quality event classifier. The segmentation of PQ disturbances, techniques for feature extraction from PQ disturbances and artificial intelligent classification techniques are covered under Sections 4–6. The effect of noise on PQ event classification and future scope are presented in Sections 7 and 8. Finally the concluding remark is included in Section 9.

## 2. Power quality

The term power quality (PQ) is generally applied to a wide variety of electromagnetic phenomena occurring within a power system network [2]. The ability of the power systems to deliver undistorted voltage, current and frequency signals is termed as quality of power supply [12]. Unexpected variation of the voltage or current from normal characteristics can damage or shut down the critical electrical equipments designed for specific purpose. Such variations happen in electrical networks with a great frequency due to a competitive environment and continuous change of power supply. In a highly evolved electrical system PQ sensitive demands can be classified as (i) digital economy (such as banking, share market and railways), (ii) continuous process manufacturing industries, and (iii) fabrication and essential services. Cost incurred to operate all the above types of loads vary from 3 to 120 per kVA per event [12]. This is huge and greatly affects economic operation of power industries. To mitigate PQ issues; customers are also equipped with some back-up instruments apart from grid supply [13]. According to IEEE standard 1159-1995 [14], the PQ disturbances include a wide range of PQ phenomena namely transient (impulsive and oscillatory), short duration variations (interruption, sag and swell), frequency variations, long duration variations (sustained under voltages and sustained over voltages) and steady state variations (harmonics, notch and flicker) with a time scale which ranges from tens of nanoseconds to steady state. Inigo Monedero et al. [15] defined PQ disturbances based on UNE standard in Spain as given in Table 1. IEEE Std. 1459-2010 [16] includes definitions for measurement of electric power quantities under sinusoidal, non-sinusoidal, balanced, and unbalanced conditions. In [17], authors presented an IEEE Std. 1459 power magnitude measurement system working as a part of a PQ improvement structure.

## 3. Automatic power quality events' classifier

Before 1990s some manual configurations were used for monitoring and managing the quality of power supply due to lack of signal processing and intelligent techniques' advancement. The decision was based on the operator/expert intuition to maintain quality within a certain range. As technology evolved, smart signal processing

**Table 1**
PQ disturbances' classification [15].

| Type | Disturbance type | | Time | Range | |
|---|---|---|---|---|---|
| | | | | Min. value | Max. value |
| Frequency | Slight deviation | | 10 s | 49.5 Hz | 50.5 Hz |
| | Severe deviation | | | 47.0 Hz | 52.0 Hz |
| Voltage | Average voltage | | 10 min | 0.85 Un | 1.1 Un |
| | Flicker | | – | – | 7% |
| | Sag | Short | 10 ms–1 s | 0.1 U | 0.9 U |
| | | Long | 1 s–1 min | | |
| | | Long-time disturbance | > 1 min | | |
| | Under voltage | Short | < 3 min | 0.99 U | |
| | | Long | > 3 min | | |
| | Swell | Temporary short | 10 ms–1 s | 1.1U | 1.5 kV |
| | | Temporary long | 1 s–1 min | | |
| | | Temporary long-time | > 1 min | | |
| | | Over voltage | < 10 ms | | 6 kV |
| Harmonics and other information signals | Harmonics | | – | THD > 8% | |
| | Information signals | | – | Included in other disturbances | |

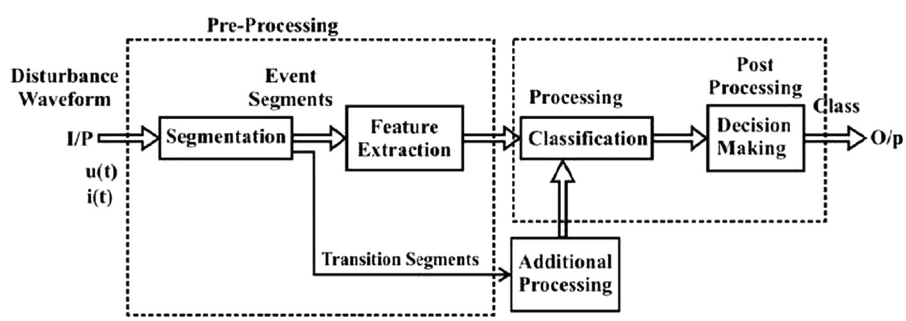


**Fig. 1.** Block diagram automatic power quality event classifier.

techniques (such as pattern-recognition, data mining, internet-networking, and artificial intelligence) with intelligent instruments (such as computers, digital signal processors, mass storage, information and communications) are adopted time to time. A basic block diagram of automatic PQ event classifier is given in Fig. 1 [18]. The disturbance signal is passed through the pre-processing unit having two function blocks; segmentation and feature extraction. The extracted features of disturbances are passed through processing unit for classification. Finally, the post-processing unit gives an actual decision regarding the type of disturbance.

## 4. Segmentation

Segmentation divides the data sequence into stationary and non-stationary parts [19]. Events are the segments in between transition segments. The feature is extracted from the event segments because the signal is stationary and normally contains the information that is unique enough to distinguish among different types of disturbances. To capture the disturbance waveform period, a triggering method is required to get start and end time instant of PQ event [20,21]. The current methods used for detecting PQ disturbances are based on a point-to-point comparison of adjacent cycle or a point-to-point comparison of the RMS values of the distorted signal with its corresponding pure signal and/or frequency domain transformed data. The recent methods proposed for this purpose are classified as parametric (or model based) and non-parametric (or transform based). The parametric methods include techniques such as Kalman filter (KF) and auto-regressive (AR) models while non-parametric techniques include short-term Fourier transform (STFT) and wavelet transform (WT) [22].

## 5. Feature extraction

Feature extraction from PQ disturbances is also known as detection of disturbances. Extracted features are used to classify the PQ events. Thereafter, the classifier's information is used to make the final decision through a post-processing unit [18]. The selection of suitable features of PQ events is extremely important for classification. Features may directly be extracted from the original measurement either from some transformed domain or from the parameters of signal models [23]. In this context, recent developments regarding feature extraction techniques are discussed in the subsections as detailed below.

### 5.1. Fourier transform based methods

The best known technique for frequency domain analysis is the Fourier transform (FT), where it represents a signal as sum of sinusoidal terms of different frequencies [24]. FT is suitable for stationary signals and extracting spectrum at specific frequencies; however it is unable to resolve any temporary information associated with fluctuations [25]. One variant of FT; the short time Fourier transform (STFT) divides the signal into small segments where each segment can be assumed to be stationary [26]. In this regard, STFT determines the sinusoidal frequency and phase contents of local sections of signal as they change over

time. Also, it extracts several frames of signals to be analyzed with a window that moves with time. With a moving window, the relation between the variance of frequency and the time can be identified [27,28]. It is difficult to analyze non-stationary signals with STFT [29]; however it has been applied to non-stationary signals when operating in a fixed window size [30]. Discrete STFT is used for time–frequency analysis of non-stationary signals. It decomposes the time-varying signals into time–frequency domain components [31]. Discrete Fourier transform (DFT) represents the discrete signals that repeat themselves in a periodic fashion from negative to positive infinity whereas fast Fourier transform (FFT) gives exactly the same result as the DFT in much less time [32].

In [33], authors presented unique features that characterize PQ events and methodologies to extract them from recorded voltage and/or current waveforms using Fourier and Wavelet Transforms (WT). In [34], authors used windowed FFT for power quality assessment. The windowed FFT is a time version of the discrete time FT. It was experimentally proved that WT is better than STFT [29]. The schemes based on STFT, S-transform, and Kalman filter have been developed efficiently for detecting PQ events [35,36].

### 5.2. S-transform based methods

The S-transform is a time–frequency tool generated by the combination of WT and STFT [37]. It produces a time–frequency representation of a time series. It uniquely combines a frequency-dependent resolution that simultaneously localizes the real and imaginary spectra. The basic function for the S-transform is Gaussian modulated co-sinusoids [38]. In the case of non-stationary disturbances with noisy data; the S-transform provides patterns that closely resemble the disturbance type and thus requires a simple classification procedure [28].

In [39], authors proposed a simple and effective method for classification and quantification of ten typical kinds of power quality disturbances using S-transform. In [40], authors presented a real-time power quality disturbances' classification by using a hybrid method based on S-transform and dynamics where the dynamics is used to reduce run time. In [41], a S-transform based neural network structure is presented for automatic classification of power quality disturbances. The S-transform technique is integrated with neural network model with multi-layer perception to construct the classifier. Power quality analysis using discrete orthogonal S-transform is presented in [42]. Multi-resolution S-transform based fuzzy recognition system for power quality events is proposed in [43]. This is based on a variable width analysis window which changes with frequency according to user defined function. In [44], authors proposed more suitable fast variants of the discrete S-transform (FDST) algorithm to accurately extract the time localized spectral characteristics of non-stationary signals.

### 5.3. Hilbert Huang transform based methods

The Hilbert Huang transform (HHT), a novel signal processing algorithm was proposed in 1998 by Dr. Huang which consists of two distinct processes [45]. The signal to be analyzed is decomposed using the empirical mode decomposition (EMD) process into intrinsic mode function (IMF) that have meaningful instantaneous frequencies and amplitudes. The EMD decomposes the signal into IMFs in such a way that the IMFs are sorted from the highest frequency to the lowest frequency. Once the signal is decomposed into IMFs, the Hilbert transform can then be applied to each IMF giving the instantaneous amplitude and instantaneous frequency versus time curve. This combination of EMD process and Hilbert transform is known as the HHT [46,47]. In a row of development, multiple HHT variants are demonstrated in the context of PQ detection and classification.

In [48], authors developed a method based on combination of EMD and Hilbert transform for assessment of power quality events. However, an approach for power quality disturbances' classification using HHT and Relevance Vector Machine (RVM) is presented in [49]. In [50], authors presented the multi-disturbance complex power quality signal HHT detection method using the HHT algorithm. In [51], a voltage flicker is analyzed using the orthogonal Hilbert Huang Transform (OHHT) instead of HHT which can be used in the analysis of nonlinear and non-stationary signals. In [52], authors proposed a novel method based on mathematical morphology and HHT which is used to detect and analyze power quality disturbances. In [53], authors presented the Hilbert-Huang method with modifications for time–frequency analysis of distorted power quality signals. In [54], authors presented a method to extract efficient features of the PQ disturbances using Hilbert Transform and to classify the disturbance signal using radial basis function (RBF) neural networks with more improved methodology.

### 5.4. Wavelet transform based methods

The wavelet transform (WT) is a mathematical tool, much like FT, that decomposes a signal into different scales with different levels of resolution by dilating a signal prototype function. The WT is based on a square-integral function and group theory representation. The WT provides a local representation (in both time and frequency) of a given signal; therefore it is suitable for analyzing a signal where time–frequency resolution is needed such as disturbance transition events in power quality [55,56]. The WT is classified into discrete wavelet transform (DWT) and continuous wavelet transform (CWT) [57].

In [58], authors introduced the use of WT and multi-resolution signal decomposition as a powerful analysis tool for PQ events. A wavelet based method for detecting, localizing, quantifying and classifying short duration PQ disturbances is presented in [59]. In [60], authors introduced a compression technique for power disturbance data via DWT and wavelet packet transform (WPT). In [61], authors proposed a model of disturbance detection for harmonics and voltages using wavelet probabilistic network which is a two-layer architecture containing the wavelet layer and the probabilistic network. Consequently, a novel approach for the PQ disturbances' classification based on the WT and self-organizing learning array system is proposed in [62]. In [63], authors introduced a new perspective for the IEEE standard 1459-2000 definitions using the stationary wavelet transform (SWT) for defining power components, power factors, and pollution factor. In [64], PQ indices that were recommended in [65] and [66] are redefined in the time frequency domain using WPT. A wavelet norm entropy based effective feature extraction method for PQ disturbance classification is presented in [67]. In [68], authors proposed a WT and S-transform based approach for islanding detection and disturbance due to load rejection in the distributed generation (DG) based hybrid system. In [69], authors introduced the un-decimated wavelet transform to compute power quantities using complex wavelet coefficients. The important issue related to the use of wavelet method is the choice of suitable wavelet. The computational cost increases with an increase in filter length. Table 2 provides characteristics of four commonly used wavelets.

### 5.5. Miscellaneous feature extraction techniques

Apart from the above techniques mentioned in Sections 5.1–5.4, some other techniques have played a significant role in PQ detection and classification. De-noising techniques with change point approach for wavelet based power quality monitoring are used and demonstrated in [70]. Parallel computing for time–frequency feature extraction of PQ disturbances is presented in [71]. Hybrid wavelet and HT

with frequency shifting decomposition for PQ analysis are presented in [72]. Several other techniques such as Gabor–Wigner transform (GT) [73], Kalman filter [74,75], Fuzzy-ARTMAP-wavelet network [76], TT Transform [77], Curve fitting [78], DWT Transform and wavelet network [79], Hybrid soft computing technique [80], parametric spectral estimation method [81], extended Kalman filtering [82], linear combiners [83], higher order statistics and case based reasoning [84], Adaline [85], digital filters [86], short-time correlation transform [87] have played an important role in PQ event detection and classification in recent years.

### 5.6. Comparative study of PQ events' detection techniques

Comparative study of PQ events' detection techniques is carried out based on critical reviews of publications [24–87]. The computational efficiency of major power quality disturbance detection techniques to detect PQ disturbances is given in Table 3. The comparison of main PQ disturbance analysis methods is detailed in Table 4.

**Table 2**
Wavelet characteristics.

| Wavelet name | Orthogonal property | Compact support | Support width | Filters length | Symmetry |
|---|---|---|---|---|---|
| Haar | ✓ | ✓ | 1 | 2 | ✓ |
| Symlets | ✓ | ✓ | 2N-1 | 2N | Near to symmetry |
| Daubechies | ✓ | ✓ | 2N-1 | 2N | Near to symmetry |
| Coiflets | ✓ | ✓ | 6N-1 | 6N | No |

N-Sample points for entire observation time.

**Table 3**
Computational efficiency of PQ detection techniques.

| Sr. no. | PQ disturbance | Percentage efficiency of PQ detection techniques | | | |
|---|---|---|---|---|---|
| | | Hilbert Huang transform [48] | S-transform [48] | Discrete wavelet transform [79] | Fast Fourier transform [156] |
| 1 | Sag | 100 | 100 | 98.67 | 95 |
| 2 | Swell | 100 | 100 | 99.33 | 98 |
| 3 | Harmonic | 95 | 100 | 99.33 | 100 |
| 4 | Flicker | 100 | 100 | 98.67 | 89 |
| 5 | Notch | 100 | 83 | 97.33 | – |
| 6 | Spike | 95 | 77 | – | – |
| 7 | Transient | 98 | 100 | 98.67 | 100 |
| 8 | (1+3) | 98 | 100 | 98.18 | – |
| 9 | (2+3) | 89 | 100 | 98.18 | – |
| 10 | (1+7) | – | – | 96.36 | – |
| 11 | (2+7) | – | – | 98.18 | – |

## 6. Artificial intelligence classification techniques

A broad definition of artificial intelligence (AI) can be the automation of activities that are associated with human thinking such as decision making, problem solving, learning, perception, and reasoning [88]. In this regard recent developments in AI tools of interest to the electric power community are detailed below.

### 6.1. Support vector machine based classification

The foundation of Support Vector Machine (SVM) has been developed by Vapnik [89], where statistical learning theory being the basis provides a new pattern recognition approach. SVMs are a set of related supervised learning methods used for classification and regression. They belong to family of generalized linear combiners [90].

In [91], authors presented an identification method for PQ events based on N-1 SVMs' classifier which is particularly effective in the automatic classification of voltage disturbances [92]. Consequently, Whei-Lin et al. [93] presented one-versus-one approach based SVM which can process the multiple classifications of PQ disturbances. The SVM method is better than optimal time frequency representation (OTFR) and is a low complexity event classifier [94]. An integrated model for recognizing PQ disturbances using wavelet multi-class SVM is presented in [95]. A SVM classifier combined with DWT to recognize the type of power system PQ is presented in [96]. The direct acyclic graph SVM correctly classifies the PQ events with high degree of accuracy and less training as well as testing times in comparison to other kernel-based learning techniques and ANN based methods [97]. The classification of PQ events based on wavelet transform and SVM is presented in [98–100]. The number of SVM and the compactness of different clusters are enhanced using modified immune optimization algorithm in classification of non-stationary power signals using modified TT-transform and SVM [101]. In [102], authors presented classification of PQ events using SVM and higher order statistical features.

### 6.2. Neural network based classification

Neural networks (NN) represent the promising new generation of information processing systems. They are good at tasks such as pattern matching, classification, function approximation, optimization and data clustering [103]. The classification and function approximation capabilities of artificial neural networks (ANN)

**Table 4**
Comparison of main methods of PQ disturbances analysis.

| Sr. no. | Method | Advantages | Disadvantages |
|---|---|---|---|
| 1 | STFT | Successfully used for stationary signals where properties of signals do not evolve in time. Simple in implementation | Not suitable for non-stationary signal as it does not track signal dynamics properly due to limitation of fixed window width |
| 2 | HHT | Useful in feature extraction of distorted waveform, generates quadrature signal by which instantaneous amplitude and phase can be easily evaluated | Limited only for narrow band conditions |
| 3 | ST | Fully convertible from time domain to 2-D frequency translation domain and then to Fourier frequency domain | Based on block processing manner and does not satisfy real-time requirement, incorrect measurement of harmonics due to dependency of frequency window width on central frequency |
| 4 | WT | Provide local representation in both time and frequency. Therefore, suitable where good time–frequency resolution is required. | Strongly influenced by noise present in the signal, suffering from spectral leakage and picket fence effects |
| 5 | GT | It has high signal to noise ratio and good time–frequency resolution | Use limited at high frequencies, computational complexity is directly associated with sampling frequency |

have been employed in power quality studies, fault, and harmonics source classification.

In [104], authors proposed and implemented a NN approach to the classification of power system disturbance waveforms. Two different NN paradigms, the common feed-forward neural network (FFNN) and time delay neural network (TDNN) are investigated. In [105], a method for automatically detecting, localizing and classifying various types of disturbance wave-shape fault is presented. A NN based approach to non-intrusive harmonic source identification is proposed in [106]. In [107], authors proposed a novel method based on wavelet and ANN for transmission line fault detection and classification using oscillo-graphic data. In [108], some patterns based on DWT are studied for detection and identification of both low frequency disturbances like flicker, harmonics, and high frequency disturbances like transient and sags. A wavelet based artificial neural network classifier for recognizing power quality disturbances is implemented and tested in [109]. In [110], a feature extraction method based on centre clustering is obtained which is used as an input to ANN for PQ event classification. PQ events' classification based on S-transform and probabilistic NN is presented in [111]. Classification of PQ events using a balanced neural tree is presented in [112]. A dual neural network based methodology to detect and classify single and combined PQ disturbances is proposed in [113]. The radial basis function (RBF) neural network for recognition and classification of PQ events is presented in [114,115].

### 6.3. Fuzzy expert system based classification

Fuzzy classification system is based on Mamdani type rules to evaluate the information provided by the linguistic variable inputs [116,117]. Fuzzy logic refers to a logic system that generalizes the classical two-valued logic for reasoning under uncertainty. It is motivated by observing that human reasoning can utilize concepts and knowledge that do not have well defined or sharp boundaries [118]. A fuzzy expert-system is an expert system that uses a collection of fuzzy sets and rules instead of Boolean sets for reasoning about data [119].

In [120], authors proposed the design of a tool to quantify PQ parameters using wavelets' and fuzzy sets' theory. A hybrid technique for characterizing PQ events using a linear Kalman filter and a fuzzy-expert system is presented in [121]. An approach for the detection and classification of single and combined PQ disturbances using fuzzy logic and a particle swarm optimization algorithm is proposed in [122]. In [123], authors presented an approach for the classification of PQ data using decision tree and chemo-tactic differential evolution based fuzzy clustering. An approach for PQ time series data mining using S-transform based fuzzy expert system is presented in [124]. In [125], authors presented an approach for the visual localization, detection and classification of various non-stationary power signals using a variety of windowing techniques. In [126], a hybrid scheme using a Fourier linear combiner and a fuzzy expert system for the classification of transient disturbance waveforms in a power system is presented. In [127], authors proposed a wavelet-based extended fuzzy reasoning approach to PQ disturbance recognition and identification. An adaptive fuzzy self-learning technique for detection of abnormal operation of electrical systems is presented in [128]. A data compression technique for power waveform using adaptive fuzzy logic is presented in [129].

### 6.4. Neuro-fuzzy system based classification

Neuro-fuzzy based methods have advantages of handling any kind of information, manage imprecise, partial, and vague or imperfect information. These methods also have advantages to resolve conflicts by collaboration and aggregation, self-learning, self-organizing and self-tuning capabilities. Further, there is no need of prior knowledge of relationship of data, mimic human decision making process, and fast computation using fuzzy number operations [130,131].

In [132], authors described a cork stopper quality classification system using morphological filtering and contour extraction by following a feature extraction method and a fuzzy-neural network as a classifier. In [133], an approach based on a four step algorithm combining 3-D space referential representation, principal component analysis and neuro-fuzzy based automatic classification is presented. Adaptive-neuro-fuzzy-inference system approach for transmission line fault classification and location is presented in [134,135]. A method for mitigation of voltage sags with phase jumps by UPQC with particle-swarm optimization (PSO) based adaptive neuro-fuzzy system is presented in [136].

### 6.5. Genetic algorithm based classification

Genetic Algorithm (GA) is a search algorithm based on the mechanics of natural selection and natural genetics. It combines survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search [137]. The GA is considered to be an excellent intelligent paradigm for optimization using a multipoint, probabilistic, random and guided search mechanism [138].

In [139], authors described an innovative and fuzzy-based adaptive approach to the metering of power and RMS voltage and current employing GA. Power system model validation for PQ assessment applications using GA is presented in [140]. The GA is introduced as a powerful tool for monitoring and supervising power system disturbances generated due to dynamic performance of power systems in [141]. In [142], a jumping genes paradigm in the format of hierarchical GA is proposed for optimizing the power voltage control systems. A new method using enhanced GA for placement of PQ monitors is proposed in [143]. An analytic method of power quality using extension GA and wavelet transform is presented in [144]. In [145], authors described the design of a GA that optimizes the S-transform for analysis and classification of the perturbations in electrical signals.

### 6.6. Miscellaneous classification systems

Detection and classification of PQ events in real-time are important considerations to electric utilities. The design and development of a rule based system for intelligent classification of PQ disturbances using S-transform features are presented in [146,147]. Rule-based and wavelet-multi-resolution decomposition for PQ events classification is presented in [148]. An expert

**Table 5**
Strength and weakness of AI techniques.

| Sr. No. | Attributes | AI techniques | | | | | |
|---|---|---|---|---|---|---|---|
| | | NN | ANN | SVM | FL | GA | ES |
| 1 | Uncertainty tolerance | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆ |
| 2 | Imprecision tolerance | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆ | ⋆ |
| 3 | Knowledge representation | ⋆ | ⋆⋆⋆⋆⋆ | ⋆ | ⋆⋆⋆ | ⋆ | ⋆⋆ |
| 4 | Adaptability | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆ | ⋆⋆⋆ | ⋆ |
| 5 | Maintainability | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆ | ⋆⋆ | ⋆ |
| 6 | Learning ability | ⋆⋆⋆ | ⋆⋆⋆⋆ | ⋆⋆⋆⋆ | ⋆ | ⋆⋆⋆ | ⋆ |
| 7 | Explanation ability | ⋆ | ⋆⋆ | ⋆ | ⋆⋆⋆ | ⋆ | ⋆⋆⋆ |
| 8 | Data mining | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆ | ⋆⋆ | ⋆ |
| 9 | Generalized Performance | ⋆⋆⋆ | ⋆⋆⋆ | ⋆⋆⋆⋆⋆ | ⋆ | ⋆ | ⋆ |

NN – Neural network, ANN – Artificial neural network, SVM – Support vector machine, FL – Fuzzy logic, GA – Genetic algorithm, ES – Expert system; AI Technique with higher number of ⋆ is more preferred for specific purpose.

**Table 6**
Comparison of PQ events classification methods.

| Sr. No. | Method | Advantages | Disadvantages |
|---|---|---|---|
| 1 | NN | High classification accuracy for mixed PQ disturbances | Less efficient under noisy conditions |
| 2 | ANN | High accuracy for real time applications and provides mathematical flexibility | Convergence speed and accuracy depends on the network architecture as well as noise in the signal |
| 3 | SVM | Potential to handle large features, provide stable solution to quadratic optimization, high learning processes | Poor classification accuracy when training samples are minimum |
| 4 | FL | Accurate in modeling and analyzing complex systems | Training set for every case is fixed, hence not suitable for new disturbances |
| 5 | GA | Accurately classify PQ disturbances generated due to dynamic performance of power system and damped sub-harmonic signals | High computational time |
| 6 | ES | Can be used with or without limited data | Expensive system, slow in execution, it is difficult to draw conclusion if assumptions and actual situations do not match exactly |

system for PQ classification is presented in [149,150]. Several other PQ classification techniques such as Warping Classifier [151], Digital filtering and mathematical morphology [152], Hardware and software architecture [153–155], Hidden Markov models and vector quantization [156], recurrence quantification analysis [157], Phasor data records and sequence of events [158], Multi-way principal component analysis [159], nearest neighbor rule [160], Transient-meter [161], Easy VI program [162], inductive inference approach [163], and fault current limiting high-temperature superconductor cable [164] have played an important role in PQ event classification in past years.

### 6.7. Comparative study of PQ events classification techniques

Comparative study of PQ events' classification techniques is carried out based on critical reviews of publications [88–164]. The strength and weakness of different AI techniques for power quality disturbance classification are analyzed and presented in Table 5. The comparison of different power quality disturbances' classification methods is provided in Table 6.

## 7. Effect of noise on PQ event classifiers

The signals captured by monitoring devices are often accompanied with noise thereby affecting the extraction of important features from the signal. Noise has an adverse effect on the performance of wavelet based event detection, time localization and classification schemes due to the difficulty of separating noise and disturbances [165]. The disturbed components of the waveform carry the most important information for detection and classification. When PQ data is decomposed using wavelet transform most of the disturbance components are reflected at higher frequency bands which are also occupied by noise. Therefore, even if the magnitude of noise level present is not very high compared to fundamental component for many PQ disturbances it is comparable to disturbance energy at these bands. Hence, the presence of noise degrades the detection capability of wavelet based PQ monitoring system [166].

In this regard, a de-noising technique with a change-point approach for wavelet-based power-quality monitoring is presented in [167]. Consequently, performance improvement of power quality disturbances' classification based on a new de-noising technique is presented in [168]. Also recognizing noise influenced PQ events with integrated feature extraction and neuro-fuzzy network is presented in [169]. In [170], authors proposed a simple yet effective de-noising technique using inter- and intra-scale dependencies of wavelet coefficients to de-noise PQ waveform data for enhanced detection and time localization of PQ disturbances. The de-noising technique with a spatial noise-suppression method for wavelet-based PQ monitoring is presented in [171].

A brief comparative study of error introduced due to the presence of noise in classification of PQ disturbances using ANN and SVM is presented in Table 7.

**Table 7**
Effect of noise on PQ classification.

| Sr. no. | PQ disturbance | Percentage error due to noise | |
|---|---|---|---|
| | | ANN | SVM |
| 1 | Sinusoidal waveform | 10.86 | 9.67 |
| 2 | Voltage sag | 8.69 | 5.43 |
| 3 | Voltage swell | 8.69 | 6.45 |
| 4 | Notch | 4.44 | 4.54 |
| 5 | Transient | 6.67 | 5.49 |

## 8. Future scope

The present thrust in PQ research is of real-time analysis; therefore many researchers have given so many enhancements in real-time detection and mitigation. However, the PQ analysis technology still has a way to grow especially for real-time PQ events. Therefore, there is a need to work on real-time PQ events to develop new techniques for classification and mitigation. There is also a need to develop a generalized approach for detection and classification of single and multiple PQ events. On this basis, it is possible to improve the study of blackout conditions.

## 9. Conclusion

A critical and comprehensive literature review on the detection and classification of PQ events in the electrical power system is carried out. This paper presents a literature survey on detection /feature extraction techniques such as wavelet transform, S-transform, Fourier transform, Hilbert-Huang transform and artificial intelligence techniques for PQ classification such as SVM, ANN, Fuzzy logic, and GA. The effect of noise on PQ event classification is also outlined. Finally, at the end of paper future scope for research in the field of power quality detection and classification techniques has been presented.

According to developed review, it can be concluded that commonly used techniques for detection of PQ disturbances are WT, ST, FT and HHT. The comparative study of these techniques will help in selecting the particular technique for specific application. Regarding event classification, trend has been the use of algorithm based on ANN,

SVM, GA, ES, and FS. The major advantages and disadvantages as well as effectiveness of the particular methods are outlined.

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